Correlation Between Crime and Street Lighting in Rochester, Minnesota USA from 2008-2013

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Abstract

This research examined relationships between crime and its proximity to street lighting in Rochester, Minnesota USA between the years of 2008-2013. A Geographic Information System (GIS) analysis using crime and street light data was conducted to provide visual representations of Hot Spots and statistical analysis. Choropleth maps identified areas of high concentrations of crime near street lights, and statistical analysis examined the statistical relationships between crime and street lighting. Statistical analysis suggested most precincts concentrated around a zero correlation value, meaning there insufficient support to conclude a correlation.

Introduction

This study started as a redistricting project for the Rochester Police Department (RPD). RPD was experiencing staff shortage and needed police zones re-designed and reduced from eighteen to fourteen. Redesigning police zones was exceedingly large in scope and research required secure access to their resources. RPD agreed that conducting an analysis on the effect of improved street lighting as a means of combating crime would be more feasible.

Contemporary interest in the relationship between street lighting and crime began in North America during the dramatic rise in crime that took place in the 1960s. Many towns and cities embarked upon major street lighting programs as a means of reducing crime and initial results were encouraging (Wright, Heilweil, Pelletier, and Dickinson, 1974). By identifying crime patterns and trends, the Rochester Police Department can improve tactical approaches to prevent crime and staff police beats accordingly.

There are two main theories of why improved street lighting may cause a reduction in crime. The first suggests that improved lighting leads to increased surveillance of potential offenders (both by improving visibility and by increasing the number of people on the street) and hence to increased deterrence of potential offenders. The second suggests improved lighting signals community investment in the area and that the area is improving, leading to increased community pride, community cohesiveness, and informal social control. The first theory predicts decreases in crime especially during the hours of darkness while the second theory predicts decreases in crime during both

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daytime and night time (Farrington and Welsh, 2002a).

Effects of improved street lighting may vary according to the demographics of the area. For example, improved lighting in a community with a relatively homogeneous population will have less impact than lighting a heterogeneous population with higher residential mobility. Effects of improved lighting may also interact with other environmental improvements such as closed circuit cameras, updated locks, and a higher police presence (Farrington and Welsh, 2002).

Purpose of this Study

The primary hypothesis guiding this study was to spatially and statistically analyze theoretical links between street lighting and crime. This evaluation could be of interest to criminal justice planners and professionals who are engaged in the designing and staffing of police zones and those installing and maintaining street lighting systems.

Study Area

In 2013 the city of Rochester, Minnesota USA occupied an area of 50.15 square miles and had a population of 110,393 with a density of 1950 people per square mile (RAEDI, 2013).

The area and units of observation were the eighteen police precincts within the city limits of Rochester, MN. ESRI's ArcGIS 10.2 software includes a Spatial Statistics toolbox with functionality for identifying spatial clusters, summarizing key characteristics of distribution, and partitioning features into similar groups. The software also helped design the graphic map of Olmsted County and Rochester's eighteen police precincts. In this study, all precincts were analyzed for correlation between crime and street lighting. Figure 1 illustrates Rochester's 18 police zones divided into subzones according to location (Figure 1).

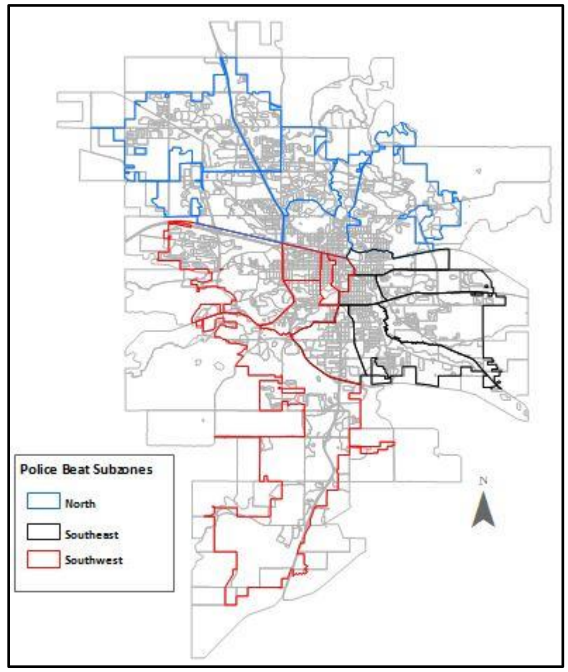


Figure 1. Police Zones Rochester, Minnesota. Data Source: Olmsted County.

Background

Projection

In a projected coordinate system, locations are identified by x,y coordinates on a grid, with the origin at the center of the grid. Each position has two values that reference it to that central location. One specifies its horizontal position and the other its vertical position. The two values are called the x-coordinate and y-coordinate (ESRI, 2006). The projected coordinate system NAD_1983_HARN _Adj_MN_Olmsted_Feet was used.

Lighting Use and Design

Technical standards for the performance of street lighting systems in the United States are put forward by the American National Standards Institute (ANSI), under the sponsorship of the Illuminating Engineering Society (IES) of North America (Tien, O'Donnell, Barnett, and Mirchandani, 1979). Although Rochester Public Utilities (RPU) follows these standards, lighting installation practices have changed over the decades leaving the lighting layout to that what was present when the area was developed.

Not all street lights emit the same amount of light. Factors such as elevation from the ground, shape of the three-dimensional emission pattern, and lumen depreciation make it nearly impossible to learn about the quality and quantity of public illumination. Conversations with RPU employees indicated light measurements are rarely made because they are time consuming and expensive. In order to compute average illumination for this study, it was necessary to make horizontal illumination measurements.

Rather than using statistical models to predict how the public space is illuminated, average horizontal illumination analysis was undertaken to determine the buffer size needed to conduct spatial analysis. In order to undertake the analyses, point-to-point calculations of foot-candles were determined. Illuminance follows the Inverse-Square Law, therefore the foot-candle calculation used the following formula:

$$FC = \frac{IxN}{D3}$$

Where:

FC=Foot-candle
I = cd (candela) towards point
D = distance to point (the square root of X2 + Y2 + Z2)
N = distance normal to the surface

The function of street lighting is to illuminate road surface, objects, and surrounding areas. Illuminance is the amount of light that reaches the road from the luminaire of the street light. Mounting height is the distance from the bulb to the surface of the road. The distance the lamp is mounted above the roadway will affect the illumination intensity, uniformity of brightness, area covered, and relative glare of the unit (Parmar, 2014).

RPU has lighting fixtures with four different mounting heights: 18, 23, 24, and 30 feet. The average foot-candle factor was obtained by averaging several points on the roadway, each of which received illumination from varying angles. RPU uses a distribution called Type II. Type II distributions provides a wide, round pattern and is more suited for small streets and wide pathways. The fixture is placed in the center of where the light is required and the light is distributed in an oval type shape around the entire fixture area. The width of the light pattern on the ground is about 1.5 times wider than the mounting height of the fixture (SEPCO, 2014). Higher mounted units provide greater coverage but lower illumination levels

Modeling the Illumination Distribution on the Street

The light distribution of the street may be modeled as the spatial variation (*x,y*) of the illuminance, in which *x* and *y* are the spatial coordinates on the roadway. Rochester street lamps are a simple setup; one luminary attached to one arm, whose optical axis points into the floor without tilt, σ = 0. In general, the 2D illuminance distribution, from a luminary inclined σ, and mounted in an arm with length d, is:

$$E(x)\ \frac{I(0-\sigma)h}{[(x-d)^2+h^2]^{3/2}},$$

where angle $\theta = \arccos\{h[(x-d)^2+h^2]^{-0.5}$ (Moreno, Avendano-Alejo, Saucedo-A, and Bugarin, 2014). Figure 2 models light distribution.

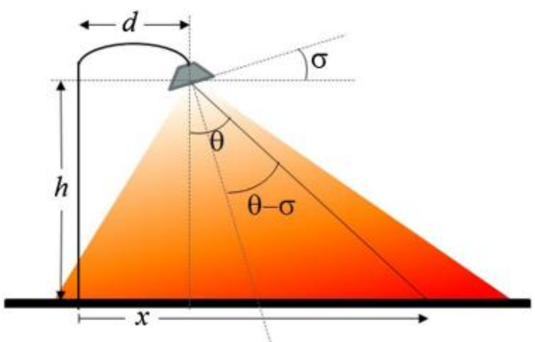


Figure 2. Modeling the Illumination Distribution on the street.

Because Rochester Public Utilities install several types of lighting fixtures with different mounting heights, a field test was conducted at a height of 6 foot 4 inches above the ground. Three foot-candles were sufficient at this height to distinguish features of any individual to a distance of 35 feet from a light pole (Figure 3).

The median foot-candle recommendations for public spaces with dark surroundings are 3 foot-candles (Guth, 2009) which authenticated the constant in the field test. Of particular importance regarding the distance used, the average frontage in the city of Rochester is 70 feet and the minimum right of way for city streets is 66 feet. The 35 foot buffer would allow respectable visibility to the center-line on most streets and visibility on half the average of a city lot frontage.

Methods

Crime Data

Crime data were obtained from the Rochester Police Department records of calls for service and reported crimes. Call data are either recorded in a database and geocoded, or collected from officer initiated activity and logged into a database for further review. This database is then used for geospatial predictive modeling to help identify locations where crimes might occur. Some attributes in the crime database did not align with the scope of this project and were eliminated from the analysis.

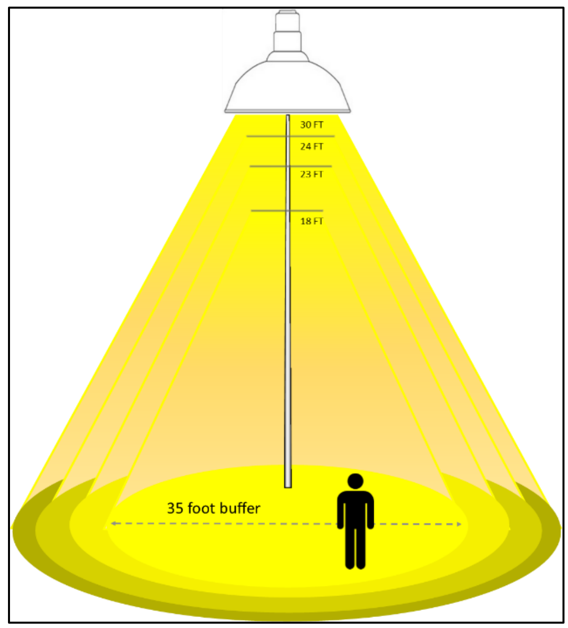


Figure 3. Average horizontal illumination analysis.

The selection of crime for this study were based on seven specific criteria: Arson, Assault, Burglary, Damage to Property, Theft, Robbery, and Trespassing. An “other” category was created to include all crimes not listed above. The crime database was edited to show only crimes that were committed between sunset and sunrise the following day.

Table 1 displays the yearly crime distribution between 2008 and 2013. Crime categories were kept separate from the overall crime count in Rochester.

Yearly breakdown of crime from Table 1 were used to calculate percentages of individual crime by year (Table 2).

Table 1. Yearly Breakdown of Crime Data.

	2008	2009	2010	2011	2012	2013
Arson	9	16	3	11	3	5
Assault	303	226	142	246	241	223
Burglary	453	282	119	291	371	327
Damage to Property	786	671	591	630	617	448
Theft	2399	2132	1086	2221	2523	2390
Robbery	49	35	21	52	51	52
Trespassing	68	90	85	73	93	84
Total Crimes in study	4067	3452	2047	3524	3899	3529
Other crimes	1815	1674	1516	1748	1689	1569
Total Crimes	5882	5126	3563	5272	5588	5098

Table 2. Percentage of Individual Crime by Year.

	2008	2009	2010	2011	2012	2013
	%	%	%	%	%	%
Arson	0.2	0.3	0.1	0.2	0.1	0.1
Assault	5.2	4.4	4	4.7	4.3	4.4
Burglary	7.7	5.5	3.3	5.5	6.6	6.4
Damage to Property	13.4	13.1	16.6	11.9	11	8.8
Theft	40.8	41.6	30.5	42.1	45.2	46.9
Robbery	0.8	0.7	0.6	1	0.9	1
Trespassing	1.2	1.8	2.4	1.4	1.7	1.6
Total Crimes in study	69.1	67.3	57.5	66.8	69.8	69.2
Other crimes	30.9	32.7	42.5	33.2	30.2	30.8

Street Light Data

Street light hours were calculated using data obtained from the U.S. Naval Observatory (USNO) Astronomical Applications Department. The USNO serves as the official source of time for the U.S. Department of Defense. Sunset and sunrise times were averaged for each week of the year. To define the week of the year and the corresponding sunrise/sunset time, individual weeks were assigned a number between one and fifty-two and merged to the crime database. To link the crime and street light databases, crime data was categorized using the same sunrise/sunset method.

The vast majority (99%) of streetlights owned and maintained by Rochester Public Utilities are controlled by individual photocells which theoretically turn on the streetlights when conditions darken and off when conditions lighten - approximately 15 minutes before sundown until 15 minutes after sunrise.

Combining the USNO data with the Rochester crime data, two fields were created labeled light on and light off. Individual incidents were assigned week numbers and the light on and light off fields were adjusted accordingly. Table 3 shows a half year of the sunrise and sunset times along with the end of week dates.

Table 3. Sunrise and Sunset times.

Week Number	Sunrise	Sunset	End of Week Date	LightOff	LightOn
1	7:51	16:45	7-Jan	8:06	16:30
2	7:49	16:53	14-Jan	8:04	16:38
3	7:45	17:02	21-Jan	8:00	16:47
4	7:40	17:07	28-Jan	7:55	16:52
5	7:30	17:23	4-Feb	7:45	17:08
6	7:22	17:33	11-Feb	7:37	17:18
7	7:11	17:43	18-Feb	7:26	17:28
8	7:00	17:52	25-Feb	7:15	17:37
9	6:49	18:03	4-Mar	7:04	17:48
10	7:35	19:11	11-Mar	7:50	18:56
11	7:22	19:20	18-Mar	7:37	19:05
12	7:10	19:30	25-Mar	7:25	19:15
13	6:57	19:42	2-Apr	7:12	19:27
14	6:44	19:47	9-Apr	6:59	19:32
15	6:31	19:56	16-Apr	6:46	19:41
16	6:19	20:05	23-Apr	6:34	19:50
17	6:08	20:14	30-Apr	6:23	19:59
18	5:57	20:22	7-May	6:12	20:07
19	5:48	20:31	14-May	6:03	20:16
20	5:40	20:39	21-May	5:55	20:24
21	5:34	20:46	28-May	5:49	20:31
22	5:29	20:52	4-Jun	5:44	20:37
23	5:26	20:58	11-Jun	5:41	20:43
24	5:25	21:01	18-Jun	5:40	20:46
25	5:26	21:03	25-Jun	5:41	20:48
26	5:29	21:03	2-Jul	5:44	20:48

Table 4 depicts how crime numbers significantly decrease when factoring only night time crime and crime that happened within the 35-foot street light buffer. Only

3.9% of night-time crime that occurred from 2008 until 2013 fell within the 35-foot street light buffer.

Table 4. Crime counts for Rochester, MN.

Year	Total number of crimes	Number of Nighttime crimes	Crimes under buffer	Crime % under light buffer
2008	4067	523	22	4.2%
2009	3452	477	22	4.6%
2010	2047	901	42	4.7%
2011	3524	974	36	2.7%
2012	3899	971	34	3.5%
2013	3529	380	17	4.5%
Total	**20518**	**4226**	**163**	**3.9%**

Analysis

Hot-Spot Analysis

To better understand the distribution of 911 calls and to identify patterns and trends, hot spot analysis was used to determine if more effective police resource allocation was possible.

Aggregated Data

Due to numerous coincident or almost coincident points in the 911 data, the Integrate with Collect Events method was applied. This method allowed features within a specified distance to be coalesced to a single point. Features within 30 feet of one another were likely at the same address but did not have the same coordinates resulting from differences in geocoding or GPS device accuracy. Thirty feet was a reasonable estimate of this error and was used as the point aggregates distance. A new feature class was created containing a count attribute indicating the number of incidents coalesced at each point.

Spatial Autocorrelation

Prior to running the Getis-Ord Gi* tool, Incremental Spatial Autocorrelation was ran to help find a distance band that reflects maximum spatial autocorrelation. Spatial autocorrelation, identified by the non-zero covariance between a pair of observations that are related in space, can cause inefficient estimation of the standard regression model parameters, and inaccuracy of the sample variance and significance tests. It may be caused by spatial dependence that is not adequately explained by the explanatory variables, systematic measurement errors or a mismatch between the spatial scale used to measure the variable and the scale at which it actually occurs (Anselin and Bera, 1998).

Getis-Ord Gi*

The Getis-Ord Gi* tool identifies statistically significant hot and cold spots. Creating a z-score, and p-value for each input feature indicates whether the observed spatial clustering of high or low values is more pronounced than one would expect in a random distribution of those same values. A z-score near zero indicates no apparent spatial clustering. The higher (or lower) the z-score, the more intense the clustering. A high z-score and small p-value for a feature indicates a spatial clustering of high values. A low negative z-score and small p-value indicates a spatial clustering of low values (ESRI, 2012).

The Getis-Ord local statistic is calculated as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}}$$

The Gi function creates a new feature class that duplicates the input feature class and adds a new Results column for the Gi z score. The Input Feature Class was the feature class for which the Hot Spot Analysis was performed. The Input field was the numeric count field and the Output Feature class received the Results field and Gi z score. A Fixed Distance Band was used so everything within a specified distance was included in the analysis. Everything outside that distance was excluded and no standardization of spatial weight was applied. 2,300 feet was used as the average distance as identified.

Inverse Distance Weighted (IDW)

IDW is an exact local deterministic interpolation technique. IDW assumes the value at an un-sampled location is a distance-weighted average of values at sampled points within a defined neighborhood surrounding the un-sampled point (Burroughs and McDonnell, 1998). The IDW interpolation technique is similar to buffer analysis as it estimates a crime count by counting all crimes occurring within a certain distance of an object.

IDW incorporates a factor to account for the relative distance of each crime event to the street light. Events are allocated a weight according to distance from the street light and the sum of these weightings provide an intensity measure. Using this method, all crime occurring within a certain distance of a street light (bandwidth) are inversely weighted. Events farther from the street light contribute a lower value to the final sum.

Statistical Significance

To determine if the result was statistically significant, statistical hypothesis testing was employed. Statistical significance is attained when a *p-value* is greater than the significance level (denoted α, alpha). The initial hypothesis was that the null hypothesis, H_0, stated there was no connection between data causing relationships between street lighting and crime. The alternate hypothesis, H_A, suggested there was a relationship between street lighting and crime. In this study an alpha level of .05 ($\alpha = 0.05$) was used as the benchmark to test for statistical significance.

Correlation

Aggregation of the street lighting and crime data into linear enumeration units allowed assessment of relationship strength between Rochester’s street light density and crime light density. Comparing the two densities yielded a moderately higher Pearson’s *r* value than expected. The highest value, zone 36, had an *r* value of 0.623. The scatter plot suggested as the number of street lights increased, so did the number of crimes. In this study, a Pearson’s r value of 0.623 indicated that high density crime areas also tend to be high density lighting areas. The scatter plot in Figure 4 represents the difference between the observed value and the fitted value provided by the model.

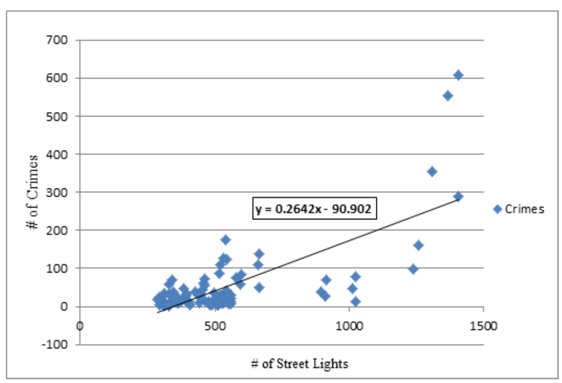


Figure 4. Scatter plot displaying the linear relationship between number of crimes and number of street lights.

Simple linear correlation was performed on the proportion of lighting against night time crime variables. Correlation coefficient values were moderately high, reaching only 0.62, suggesting there was a minimal linear association between the magnitudes of the two variables. The coefficient of determination is a statistic that quantifies the percentage of variability that is explained by the independent variables and may be considered to be a measure of the strength of the straight-line relationship (Zar, 2010). In this case, the variability in crime was minimally explained by lighting conditions.

Results

Hot-Spot Analysis

Spatial Autocorrelation

Finding hot spots at the local, neighborhood scale was a goal of this work, so the first peak with the smallest distance (2300 feet) was appropriate for all years. Figure 5 shows results of the spatial autocorrelation by distance analysis.

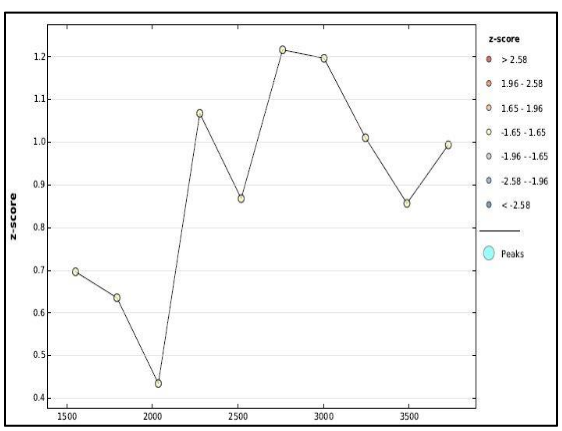


Figure 5. Spatial autocorrelation by distance.

IDW interpolation models for crime and street light data yielded interesting findings. The concentration of incidents was limited to two geographical areas in all six years. Hotspot for years 2008 through 2011 were predominantly located around Cub Foods in southeast Rochester. In the years 2010 and 2011, the hot spots migrated to areas around Kmart – also in southeast Rochester. Figure 6 shows hot spots for year, 2008. Years 2009-2011 yielded similar depictions.

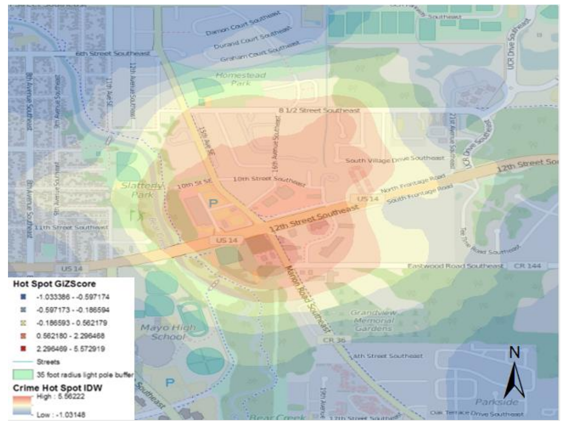


Figure 6. 2008 Hot Spot Analysis for Rochester, Minnesota. Note the area of concern (in red) is southeast Rochester around the Cub Foods area.

Figure 7 demonstrates how in years 2012 and 2013, the crime pattern shifted to the Kmart/Mayo Civic Center area.

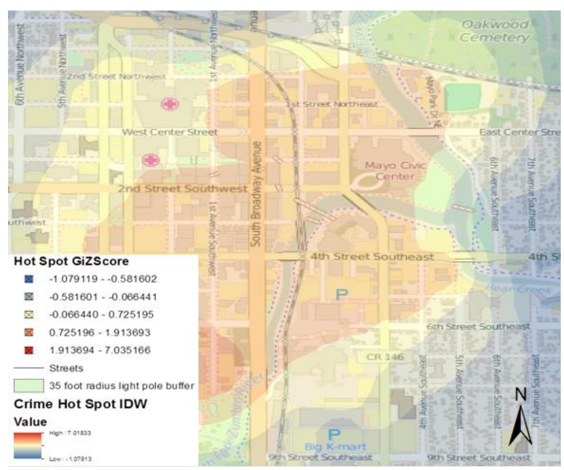


Figure 7. 2013 Hot Spot Analysis for Rochester, Minnesota. Note the area of concern (in red) is southeast Rochester around Kmart and Mayo Civic Center.

Compared to the overall crime rate and size of the city, Rochester has minimal night time crime occurring within the 35-

foot buffer. Hot Spot analysis works best when the Input Feature class contains at least 30 features, any less than 30 and the results may be unreliable. Extracting night time crime data and crimes that fell within the buffer, yielded only 30 crimes throughout the six-year period, making the results suspect.

One of the disadvantages of the Getis-Ord Gi*/HotSpot Analysis statistic is that the results are highly dependent on the size of the features being analyzed. Because the study area included a vast amount of open space, RPU's lighting infrastructure was not delineated by the boundaries. This lead to bias in mapping and therefore an alternate spatial analysis tool was used to help further explore the hypothesis.

Statistical Significance

The p-value for the t-test of the hypothesis H: $\mu = 0$ was larger than the 5% risk assumed. There was not enough variance within the samples to conclude a statistically significant relationship with the dependent variable; therefore, it could not be concluded a significant difference existed.

Correlation

A buffer of 70 feet from the centerline of streets within the City of Rochester was used to narrow the area being studied. Each buffer was then subdivided into one of the eighteen police precincts to better understand the correlation of crime and lighting in each precinct. Accepting only the lighting points within the newly assigned buffer and the crime points that were geocoded within that buffer, one standard correlation was used.

By determining the number of lights per square mile compared to the number of crimes per square mile within the buffer each year, one can get a sense of the relationship between the two variables. Table 5 shows the correlation coefficient and coefficient of determination by the zones defined by the RPD.

Table 5. Correlation coefficient and coefficient of determination by zone for all six years.

Zone	Correlation Coefficient (r)	Coefficient of Determination (r^2)
11	0.4	0.16
12	0.13	0.01
13	-0.59	0.34
14	0.19	0.03
15	-0.09	0.01
16	0.27	0.07
21	0.27	0.07
22	0.05	0.01
23	0.28	0.07
24	0.27	0.07
25	0.42	0.17
26	0.49	0.24
31	0.34	0.12
32	0.41	0.17
33	0.06	0.01
34	-0.3	0.09
35	-0.06	0.01
36	0.78	0.62

In a correlation test, a negative correlation value close to -1 would support the alternate hypothesis H_a: more street lights = less night time crime, to be true. However, in this study there were only 3 precincts in the City of Rochester that had a negative correlation. On the opposite side, there were many precincts that were in fact positive correlations, but only one of the precincts had a substantially positive value.

If Ha were true, results would have shown as the number of lights in an area increased, the number of crimes would have decreased. Most of the precincts concentrated around a zero value which means there was no correlation between street lighting within the buffer to the crimes within the buffer that could be substantiated.

Discussion

Possible Sources of Error

Data Validity

While some law enforcement agencies practice consistently good reporting, other agencies do not. As with any analysis, the conclusion can be only as good as the data on which it is based. Some limitations of this study revolve around the realization that there is little way to associate a crime event with an exact time. If the dispatcher enters the time of the call and not the actual time of the crime, the call for service would be inaccurately represented with respect to timeframe.

Data Privacy

Recognizing that potential privacy concerns could arise from using real-life crime statistics, an agreement was signed with RPD ensuring the confidentiality of individuals listed in the crime reports. First and last names were omitted from the analysis.

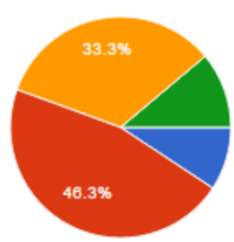
Predictive Policing

Predictive policing tries to harness the power of information, geospatial technologies and evidence-based intervention models to reduce crime and improve public safety (Perry, McInnis, Price, Smith, and Hollywood, 2013). The RPD has been proactive in predictive policing. Using models supported by prior crime and street light data, the RPD has been able to reduce the number of crime incidents and therefore reduce the crime hotspots from year to year. The success of predictive policing is highly dependent on the reliability of the data. Crime, street light data and how to fuse that data together are all interconnected.

Suggestions for Future Research

No method provides a perfect view on the relationship between crime and street lighting. Further research is required to account for neighborhood demographics, socio-demographic conditions and to quantify the spatial range over which poor lighting maintains an influence on quality of life in the community.

A subsidiary component of this study originally planned to assess effects street lighting had on the fear of crime. Fifty-six Rochester residents were surveyed and asked multiple questions about how they viewed their personal safety in Rochester. Only five percent of population being questioned stated they feel unsafe walking at night. Forty-four percent were concerned someone would steal or damage their property and thirty-two percent were concerned someone would break into their home (Figure 8).

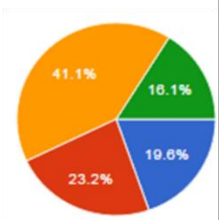


	# responses	% of responses
Someone will hurt you or your family	5	8.9%
Someone will still and/or damage your property	25	44.6%
Someone will break into your home	28	32.1%
Someone will rob me	6	10.7%

Figure 8. Responses from Rochester residents.

Figure 9 shows that forty-one percent of respondents thought more neighborhood watch programs would be the most effective crime-reducing method.

After initial and further analysis and exploration, it was concluded this topic was far too broad and did not yield statistical confirmation to accept or reject a hypothesis. As such, while originally part of the design, this survey yielded an insufficient approach and the design was modified accordingly to account for more specific and available data for greater exploration. The concept would be very advantageous if comparing the influence of street lighting on crime and fear of crime.



	# responses	% of responses
More policing	11	19.6%
More street lighting	13	23.2%
More neighborhood watch programs	23	41.1%
Having a dog	9	16.1%

Figure 9. Summary of crime-reducing measures considered most effective.

Conclusion

In this study, the null hypothesis, H_0, suggests the data were random and that no causation or influence existed between the street lighting and crime between the years of 2008 and 2013. Attention was focused principally on a group of crimes considered likely to be affected by night time influences and within a thirty-five foot light pole buffer. Correspondingly, street lights are only switched on at night and can only conceivably affect crimes when they are illuminated.

While lighting may help improve an area, better lighting by itself has very little effect on crime, and in fact, may often displace crime from lit areas to other places. The renovation of a highly noticeable component of the physical environment combined with changed social dynamics may act as a psychological deterrent. Potential offenders may judge that the image of the location is improving and that social control, order, and surveillance have increased (Taylor and Gottfredson, 1986). Despite the fact this assumption has little statistical validation, one's intuition that street lighting makes an environment less intimidating provides a crushing argument in support of the assumption.

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